A NEURAL NETWORK METHODOLOGY FOR ISCHAEMIA DETECTION IN LONG DURATION ELECTROCARDIOGRAMS

C. Papaloukas, D.I. Fotiadis, A. Likas and L.K. Michalis

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Department of Computer Science
University of Ioannina
45110 Ioannina, Greece

A neural network methodology for ischaemia detection in long duration electrocardiograms

C. Papaloukas[1], D.I. Fotiadis[2], A. Likas[2] and L.K. Michalis[3]

[1]Department of Medical Physics, Medical School, University of Ioannina
[2]Department of Computer Science, University of Ioannina
[3]Department of Cardiology, Medical School, University of Ioannina
Ioannina, Greece

ABSTRACT: The development of an artificial neural network model is studied for the classification of the cardiac beats as ischaemic or not. The network is designed to be part of a more general algorithmic schema, which detects ischaemic episodes in long duration electrocardiographic recordings. An interval from the recorded signal containing both the ST segment and the T wave is the input to the network. Due to the large dimension of the input vector, principal component analysis was adopted and any redundant features were eliminated. Different feed-forward neural network architectures were examined after modifying the number of nodes in the hidden and input layers. Also, various algorithms were applied for network training. A task specific cardiac beat database was developed in collaboration with three medical experts in order to perform network training and testing. This database contains excerpts from the European Society of Cardiology ST-T database which were diagnosed beat-by-beat from the three experienced cardiologists. The efficiency of each network was tested in terms of sensitivity and specificity. The results show that the employed method can classify the cardiac beats more accurately than other reported techniques.

INTRODUCTION

Myocardial ischaemia is the most common cause of death in the industrialised countries. It is caused by insufficient blood flow to the muscle tissue of the heart. This reduced blood supply may be due to narrowing of the coronary arteries, obstruction by a thrombus, or less commonly, to diffuse narrowing of arterioles and other small vessels within the heart. In the electrocardiographic (ECG) signal ischaemia is expressed as slow dynamic changes of the ST segment and/or the T wave [1,2]. Long duration electrocardiography, like Holter recordings or continuous ECG monitoring in the coronary care unit, is a simple and non-invasive method to observe such alterations. The development of suitable analysis techniques can also make this method a very effective one.

ECG has 3 main waveforms: the P wave, the QRS complex and the T wave (Figure 1). P wave corresponds to the sequential activation (depolarization) of the right and left atria, QRS complex to the right and left ventricular depolarization (normally the ventricles are activated simultaneously) and the ST segment with the T wave to the ventricular repolarization. In order to detect ischaemic episodes, the ST segment and the T wave need to be evaluated. The evaluation process can be based upon medical knowledge, where a set of rules is applied, [3-7], artificial neural networks [8-12], fuzzy logic [13,14], wavelet theory [15,16] or other signal processing techniques [17-19]. The performance of these techniques depends on the correct cardiac beat classification and the accurate episode definition. The problem with beat classification is that different doctors can make contrary diagnoses for some beat waveforms. This directly reflects to episode detection where sequences of ischaemic beats need to be assessed in order the margins of the episode to be defined.

The knowledge-based approach has been implemented on a previous work [6] with very good results. A set of rules was developed and the threshold values used by the rules were provided from the doctors' experience. However, there are more sophisticated methods to address the problem of ischaemia detection, especially in what concerns the cardiac beat classification. Use of predefined threshold values is a rigid method to study the dynamic ECG changes of ischaemic episodes.

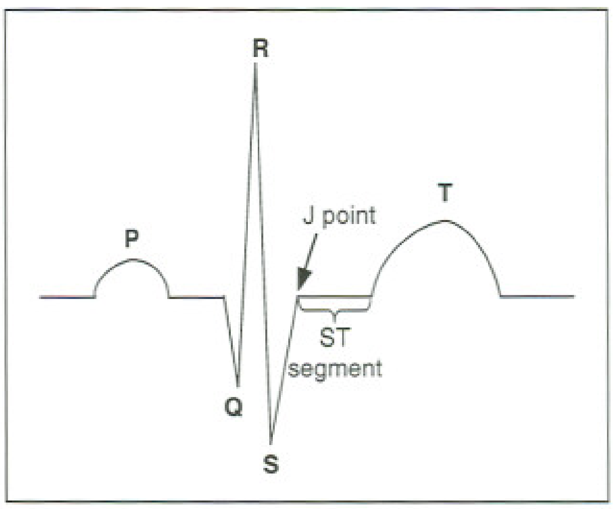

Figure 1: ECG cardiac beat.

Aiming at a more accurate classification of the cardiac beats as normal or ischaemic, the development of an artificial neural network model is studied in the present work. Instead of using doctors' experience to define and adjust the set of rules we used it to construct a dataset and train an artificial neural network. The training and testing sets were developed in collaboration with three medical experts who diagnosed in beat-by-beat mode 11 h of two-channel ECG recordings. The constructed feed-forward neural network was used to classify each beat as ischaemic or normal. The network's input was an ECG interval containing both the ST segment and the T wave, but due to the large dimension of this input vector a principal component analysis was adopted for dimensionality reduction. In order to properly adjust the network, various architectures were tested as well as different training algorithms.

MATERIALS AND METHODS

The proposed overall algorithmic schema for ischaemic episode detection can be divided into four stages (Figure 2). In the first stage the ECG signal is preprocessed and the noise is successfully filtered. ECG has three basic types of noise: baseline wandering, A/C interference and electromyographic contamination (Figure 3). Baseline wandering is a slow type of noise and can be approximated for each cardiac beat separately by a first order polynomial [20]. The subtraction of this polynomial from the recorded beat can eliminate the baseline wandering effect. A/C interference and electromyographic contamination are handled by the application of a 20 ms averaging filter. To be more precise, the above filter is applied around the area of the J point (start of the ST segment). Using an edge detection algorithm [21] and the averaged signal, J point is accurately detected. Cardiac beats that contain substantial amount of noise (J point cannot be defined) are rejected at this stage.

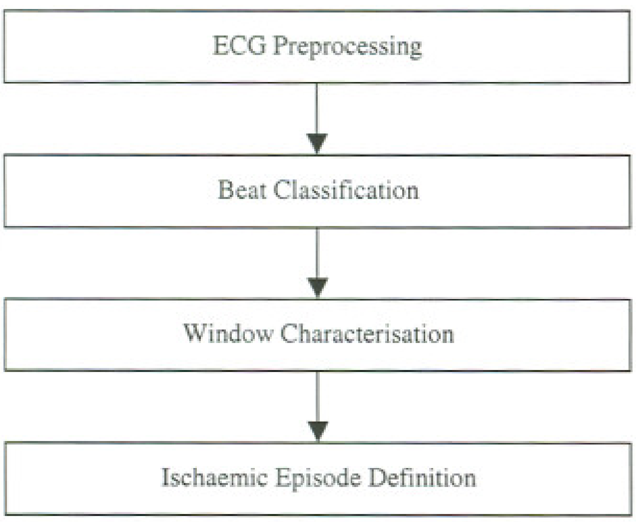

Figure 2: The four-stage algorithm.

For the beat classification stage a feed-forward neural network (multilayer perceptron) with one hidden layer was utilised. The interval ST-T = [J, J400] of the filtered ECG signal was the input vector to the network. J400 is the point that lies 400 ms after J. It also corresponds to a point that lies approximately after the offset of the T wave. The exact location of this point depends on the heart rate. The large dimension of the input pattern (100 data points, when 250 Hz is used as sampling frequency) would introduce great difficulties in the network's training. For this reason, we applied a dimension reduction technique to the input vector using principal component analysis (PCA). The overall neural network architecture is shown in Figure 4.

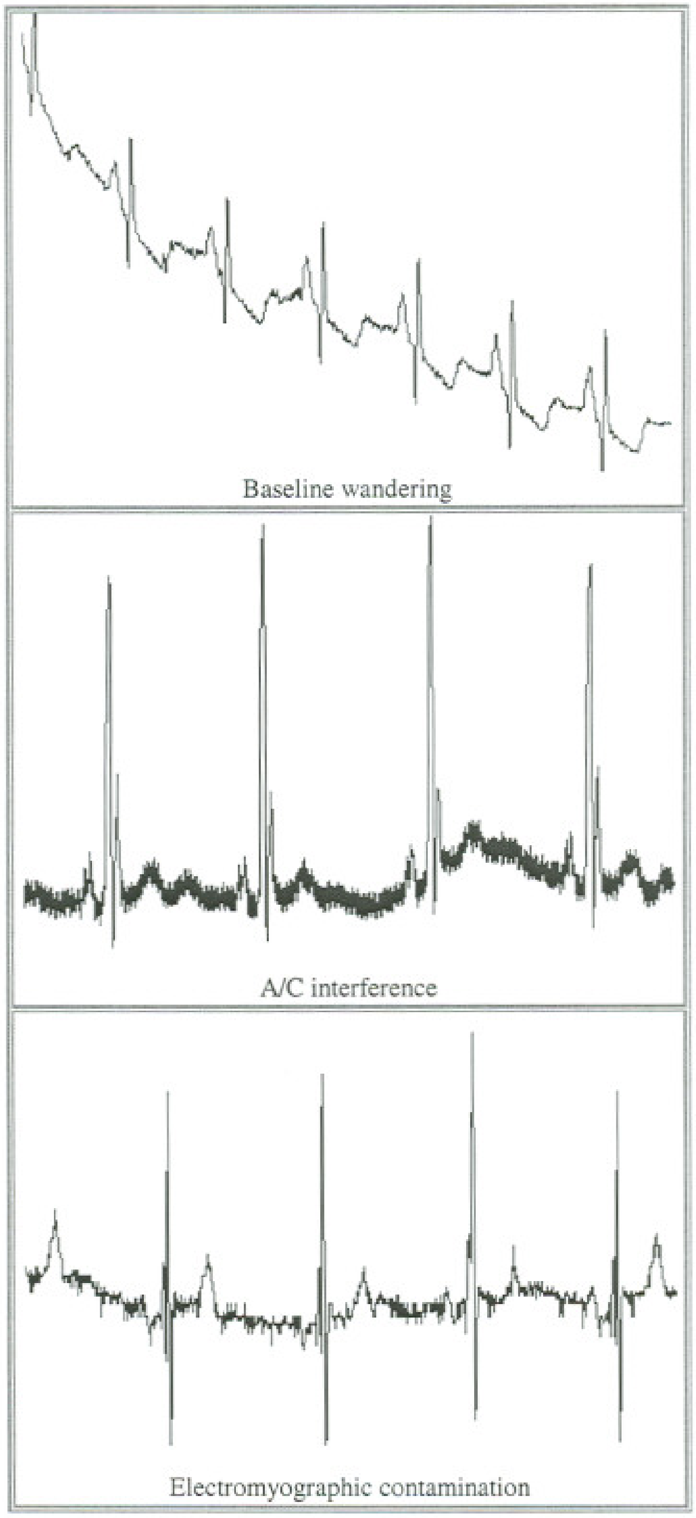

Figure 3: The three types of ECG noise.

At the third stage we constitute windows with cardiac beats of approximately 30 seconds in duration (following the European Society of Cardiology recommendations). A sliding adaptive window technique is applied to every available lead and each constructed window is characterised as normal or ischaemic depending on the percentage of ischaemic beats contained in it (more than 75%). In the last stage all the consecutive ischaemic windows are merged and the overall ischaemic episodes are defined.

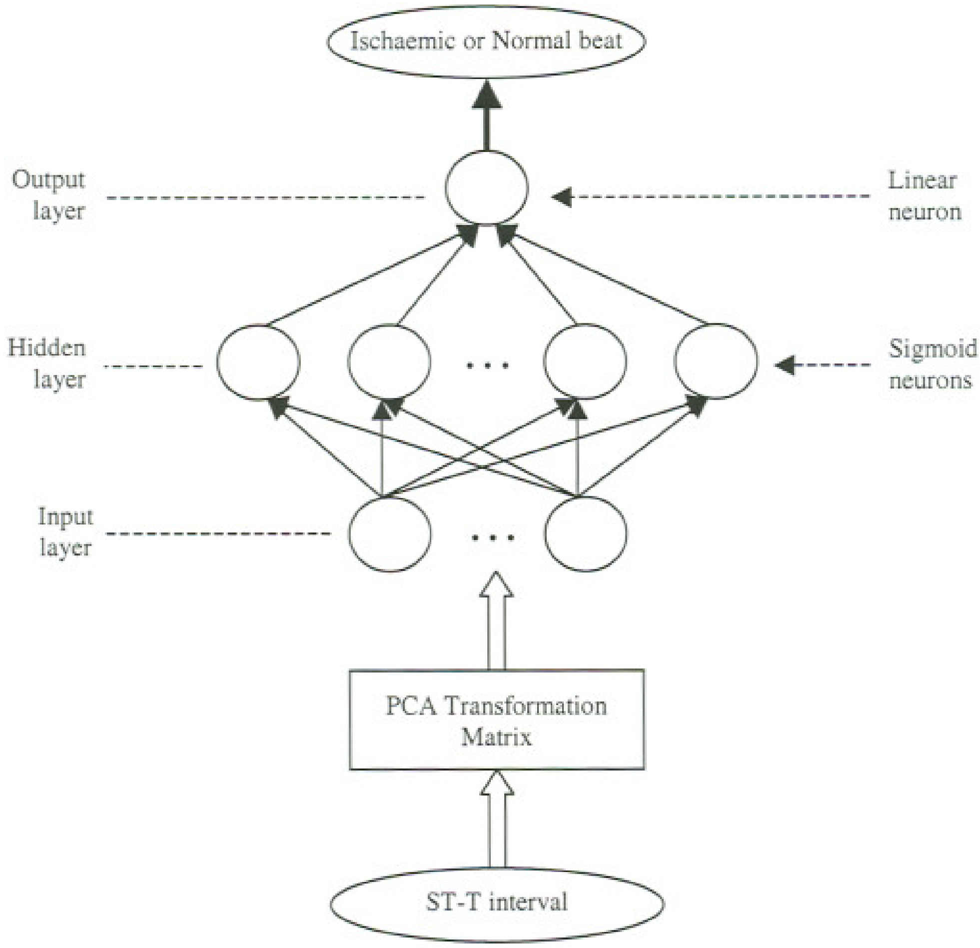

Figure 4: The artificial neural network architecture for beat classification.

The first, third and fourth stages of the overall algorithm have been studied in a previous work [6] where a rule-based method was used for beat classification. In this framework each cardiac beat was classified depending on the values of four ECG features:

i) ST segment deviation from the isoelectric line (this line defines the zero voltage).
ii) ST segment slope.
iii) T wave amplitude deviation.
iv) T wave polarity.

Currently, the second stage is examined by means of developing an artificial neural architecture capable of classifying the cardiac beats as ischaemic or not. Different network architectures were tested after varying the number of nodes in the hidden layer and also the dimensionality reduction percentage. PCA produces the amount of contribution of each component to the total variance in the training set. The overall amount of the desired contribution determines the number of the principal components. Different threshold values for this amount were used providing different dimensions of the network's input vector. Furthermore, several techniques were examined for network training:

i) gradient descent with adaptive learning rate and momentum [22],
ii) resilient backpropagation [23],
iii) scaled conjugate gradient [24],
iv) BFGS quasi-Newton [25],
v) one step secant [26],
vi) Levenberg-Marquardt [27] and
vii) Bayesian regularisation [28,29].

For the training and testing of the network we developed a task-specific ECG database based on the recordings of the European Society of Cardiology ST-T (ESC ST-T) database [30]. 11 hours of continuous two-channel recordings were extracted from 10 representative files of the ESC ST-T database (whole e0104 recording and the first hour of the e0103, e0105, e0108, e0113, e0114, e0147, e0159, e0162 and e0206 recordings). The excerpts were diagnosed in beat-by-beat mode from three experienced cardiologists of the University hospital. This accumulated experience yielded in a dataset of 86,384 cardiac beats characterised as normal, ischaemic or artefact. From these beats those that are not detected by the utilised QRS detector [6] and the artefacts were rejected, leaving a total of 76,989 beats. 37,663 beats from the final dataset (48.92%) were characterised as ischaemic and the remaining as normal. The training set was constructed after selecting the first beat out of a sequence of 40 (2.5% of the final dataset) and contained 954 ischaemic beats and 982 normal. The remaining beats were used as test set.

RESULTS

In order to study the efficiency of the proposed ANN architecture several experiments were performed. Sensitivity (Se) and specificity (Sp) were the performance measures used to evaluate the method with the data of the test set. Sensitivity is the fraction of correctly detected ischaemic beats and is given by the following formula:

$$Se = \frac{TP}{TP + FN}$$

where TP is the number of beats correctly classified as ischaemic while FN is the number of beats falsely classified as normal. Specificity is the fraction of beats correctly defined as normal and is given by:

$$Sp = \frac{TN}{TN + FP}$$

where TN is the number of beats correctly classified as normal and FP is the number of beats falsely classified as ischemic.

Multilayer perceptrons with 10 and 25 nodes in the hidden layer were tested. Initially, the amount of total contribution of the components to the variance in the training set was chosen to be 95% (only the components that contribute 95%, in total, will be used and the remaining will be rejected). The above threshold resulted in four principal components reducing the dimension of the input vector from 100 to four. When the threshold was set to 90%, PCA produced three principal components and when it was set to 97.5%, it produced six.

Table 1 shows the sensitivity and specificity for each one of the seven training algorithms, mentioned in the previous section, when the PCA threshold is 95% and the hidden layer has 10 nodes ($4\times 10\times 1$ network architecture). Table 2 has the same results but for a $4\times 25\times 1$ neural network architecture. Tables 3 and 4 examine the modification of the PCA threshold. This time the employed training algorithms are four: resilient backpropagation, scaled conjugate gradient, Levenberg-Marquardt and Bayesian regularisation. In Table 3 the PCA threshold is 90% ($3\times 10\times 1$ architecture) while in Table 4 it is 97.5% ($6\times 10\times 1$ architecture).

It is apparent from Tables 1 and 2 that when the number of nodes in the hidden layer increases, the network's performance slightly increases also. The same is observed also in Tables 3 and 4, where the input vector encloses more information for the presented beat (larger percentage threshold during PCA). Nevertheless, this improvement is not significant leading to a conclusion that 10 nodes in the hidden layer and 95% threshold for PCA (four input nodes, in accordance with the four ECG features used in the knowledge based approach) can sufficiently address the problem of cardiac beat classification when ischaemia is under study. As for the training algorithm, mainly the Levenberg-Marquardt algorithm and the Bayesian regularisation method produced the best results. We believe that Bayesian regularisation should be the most appropriate for ischaemia detection, since it has been proven to have very good generalisation capabilities [28,29]. It should be noted, that when a set of rules based upon medical knowledge [6] was used to classify the cardiac beats, the obtained sensitivity and specificity were 70.13% and 62.98%, respectively.

DISCUSSION

ECG is one of the most common signals in the everyday medical practise. This is mainly due to its simple acquisition and non-invasive nature. In addition, ischaemia is the most

Table 1: Sensitivity (Se) and specificity (Sp) for a neural network architecture with 10 hidden and four input nodes using different training algorithms.

Number of nodes in the hidden layer:	**10**	
PCA percentage threshold:	**95%**	
Training algorithm	**Se (%)**	**Sp (%)**
Gradient descent with adaptive learning rate and momentum	88.22	89.83
Resilient backpropagation	88.82	87.64
Scaled conjugate gradient	88.44	88.20
BFGS quasi-Newton	90.21	89.06
One step secant	86.67	90.06
Levenberg-Marquardt	89.60	89.15
Bayesian regularisation	89.62	89.65

Table 2: Sensitivity (Se) and specificity (Sp) for a neural network architecture with 25 hidden and four input nodes using different training algorithms.

Number of nodes in the hidden layer:	**25**	
PCA percentage threshold:	**95%**	
Training algorithm	**Se (%)**	**Sp (%)**
Gradient descent with adaptive learning rate and momentum	87.45	90.18
Resilient backpropagation	90.26	90.89
Scaled conjugate gradient	90.42	90.23
BFGS quasi-Newton	89.59	89.25
One step secant	89.39	89.11
Levenberg-Marquardt	90.84	89.24
Bayesian regularisation	90.54	89.76

Table 3: Sensitivity (Se) and specificity (Sp) for a neural network architecture with 10 hidden and three input nodes using different training algorithms.

Number of nodes in the hidden layer:	**10**	
PCA percentage threshold:	**90%**	
Training algorithm	**Se (%)**	**Sp (%)**
Resilient backpropagation	88.78	87.95
Scaled conjugate gradient	88.98	88.90
Levenberg-Marquardt	87.45	87.10
Bayesian regularisation	88.49	88.97

Table 4: Sensitivity (Se) and specificity (Sp) for a neural network architecture with 10 hidden and six input nodes using different training algorithms.

Number of nodes in the hidden layer:	**10**	
PCA percentage threshold:	**97.5%**	
Training algorithm	**Se (%)**	**Sp (%)**
Resilient backpropagation	90.79	92.03
Scaled conjugate gradient	91.63	93.06
Levenberg-Marquardt	88.76	89.51
Bayesian regularisation	91.83	90.85

common cardiac disorder. As a result, many efforts have been made during the last decades for the automated detection of ischaemia. These efforts were based on rule-based systems [3-7], artificial neural networks [8-12], fuzzy expert systems [13,14] or various signal processing techniques [15-19]. In those works two problems have to be addressed: cardiac beat classification and ischaemic episode definition. An improper beat classification procedure will directly affect the accurate definition of the episode.

Currently, we study an artificial neural network methodology for the classification of recorded cardiac beats in long duration ECGs. The obtained results are better than those of other similar approaches [6,11] in terms of both sensitivity and specificity. It should be noted that in [11], data from the ESC ST-T database were also used, but the employed recordings were not diagnosed beat-by-beat. Each annotated ischaemic episode in the database was considered to contain only ischaemic beats and this was used as the golden standard to test their method. Apparently, this is not a valid assumption, since ischaemic episodes in several cases contain some normal beats as well.

Different feed-forward neural networks were trained using several training algorithms. The ST-T interval was the input to all the designed networks, but due to its large dimension PCA was employed to eliminate any redundant features. In every experiment that was carried out, the cardiac beats were classified very accurately (high scores were obtained for both sensitivity and specificity). The task specific database that was developed played an essential role for the achieved performance. Similarly, the rejection of artefacts from the training process assisted in the proper adjustment of the network weights.

The network's performance can be further improved. The main reason for the incorrect beat classification was the wrong detection of the J point. When this happened, the network's input vector contained a shifted ECG interval, other than the ST-T, and the classification was produced more or less randomly. In order the J point to be accurately detected, more sophisticated filtering techniques are needed. Modern ECG recorders acquire less noisy signals than those included in the ESC ST-T database and consequently the proposed method is expected to perform better. Also, in order for the described neural network architecture to be used in clinical practice, the developed cardiac beat database should be extended and additional types of ischaemic and normal ECG waveform patterns should be included.

CONCLUSIONS

We propose a neural network method for cardiac beat classification that combines a feed-forward network with a dimension reduction technique (PCA). The network can be used as part of an ischaemic episode detection algorithm. It was trained using information extracted from ECG recordings and more specifically using data from both the ST segment and the T wave. The rejection of artefacts in the first stage of the method is very crucial for the network's performance. Also, the task-specific ECG database contributed significantly to the construction of effective networks. Comparative results with other proposed techniques, indicate that the presented neural network approach is superior.

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